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A Framework for Semi-Automated Generation of a Virtual Combine Harvester

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Abstract:
This paper describes a generic data-driven model of the threshing, separation and cleaning process in a combine harvester. The aim is a model that describes the actual material flow and sensor values for relevant actuator configurations and measured environmental disturbances in order to facilitate Hardware In the Loop (HIL) simulation and sensor based material flow estimation. A modular data-driven model structure is chosen as it maintains the actual steady-state values and facilitates verification and debugging using laboratory and field data. The overall model structure, model generation procedure, and estimation of parameters from field data are described, as well as simulation results are presented.

Keywords: Combine Harvester, Plant Modelling, Virtual Combine

1. INTRODUCTION

Combine harvesters are harvesting various crop types under varying environmental conditions all over the world. The threshing, separation and cleaning sub-processes should be adjusted continuously by the operator in order to optimise yield and crop quality. However actuator settings are often not accommodated due to lack of operator experience or information about the harvesting process. These processes are assigned to numerous uncontrollable biological variables and many of the optimisation parameters are even conflicting. Like loss, throughput, tailings, straw quality, grain cleanliness and power consumption. The aim is to obtain a total material flow model in order to increase the general process knowledge as well as facilitating HIL simulations and estimation of non-measurable process variables. The model inputs will be are material flows, biological parameters and actuators settings, and the outputs will be internal material flows, material residue flows and sensor readings.

Previous research has focused on an overall model structure with sub-models for threshing, separation, grain pans, cleaning shoe and return system, (Eggerl et al., 2010) and (Maertens et al., 2001). In addition to this a variety of sub-models has been presented for material distribution, throughput estimation and simulation purposes.

Within the last decade advances within sensor technologies have been driven by the desire for increased process transparency for the operator and towards computer based systems for automatic adjustments of the machine settings for threshing, separation, and cleaning system. The focus is not to generate an advanced Computational Fluid Dynamics (CFD) model (Korn et al., 2013), but a material flow model that facilitates state estimation and simulations to the executed in real-time.

A generic procedure for mapping interdependencies between material flow, actuator excitation and sensor measurements on a combine harvester was presented by Craessaerts et al. (2007a) and Craessaerts et al. (2007b). Literature summaries for material separation and loss models are found in Kutzbach (2003) and Miu (2003).

Based on laboratory and field data from a threshing and separation unit Maertens and Baerdemaeker (2003) has compared mathematical separation models from literature and Maertens et al. (2003) has compared throughput-to-loss models from literature.

Based on 250 cleaning shoe laboratory experiments Miu (2003) has shown a coefficient of determination of $R^2 \geq 0.99$ using a Weibull separation model, Craessaerts et al. (2008) presented af Fuzzy model for MOG content in the grain bin, and Craessaerts et al. (2010) presented a Fuzzy model for prediction of sieve losses.

The paper is structured as follows. Model block diagram and component description are given in Section 2. Model variables and the model generation procedure is outlined in Section 3. Acquisition of dynamic, steady-state, and stochastic model parameters from field data is described in Section 4. Simulation results from the obtained model parameters are presented in Section 5.

2. MODEL STRUCTURE

The crop processing in a combine harvesters is divided into three processes: threshing, separation and cleaning, see Fig. 1. The threshing and separation process is combined

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mechanically into one unit whether is a traditional configuration of transverse threshing rotor with straw walker separation, a hybrid configuration with transverse threshing rotor and longitudinal separation rotor, or an axial configuration with threshing and separation on the same longitudinal rotor. The resisting blocks are a traditional cleaning system with two sieves and one fan, grain pans delivering material from the threshing and separation process to the cleaning system at one single point, and a tailings return system. The overall philosophy of the model design is to facilitate high modularity with respect to the individual process modules and sensors, hence

- All modules can be built individually and compiled to the virtual combine
- Data obtained from laboratory and field can be combined
- New sensors can be included without re-acquiring all process data

The modelled state variables are actual material flows of grain or Material Others than Grain (MOG) in (ton/h), which facilitate verification using obtained laboratory and field data. In between model inputs and outputs the steady-state (static) material flows are modelled with a grey-box model structure, where parameters are fitted to a mathematical description using experimental laboratory and field data, i.e. a data-driven model. The mathematical description is based on expressions from literature and findings from experimental data.

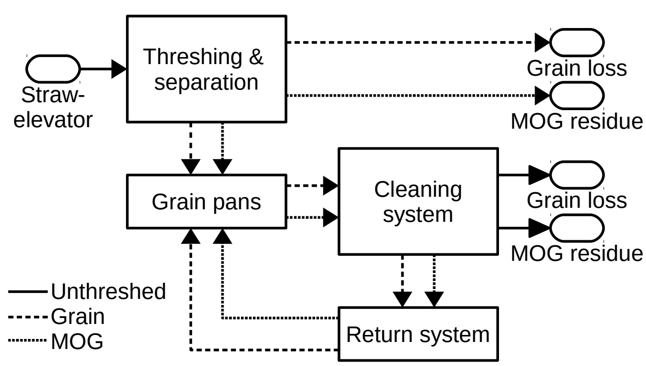

Fig. 1. Generic combine model

The virtual combine harvester functions as a basic tool that facilitates design of a variety of functionalities as

- Sensor fusion and material flow estimation
- Model based control
- Actuator, system, and sensor fault detection
- HIL simulation and virtual sensors
- Operator training

The model is built from four basic building blocks, see Fig. 2. First order average filters are used to model the dynamic part of material flows, e.g. characterising cleaning shoe material flow dynamics, fan speed dynamic response and sensor response. Time delays are used to model material transport delays, e.g. in the tailings return system and grain elevator for the yield sensor. The dynamic parameters are assumed to be reasonably consistent through various crop types, as it primarily depends on the speed of rotors, augers, and elevators on the combine. The third

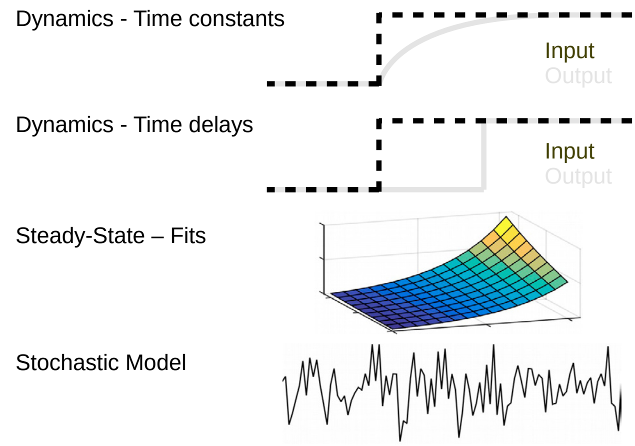

Fig. 2. Building blocks for generic combine model

block is the fitted trends for static material flow and sensor response based on laboratory and field data, e.g characterising a relation from throughput to loss, fan speed to tailings flow or tailings flow to sensor reading. Together with the dynamic parameters the material flow is modelled using the Wiener model method (Nelles, 2001), see Fig. 3. The fourth building block is the stochastic noise from crop

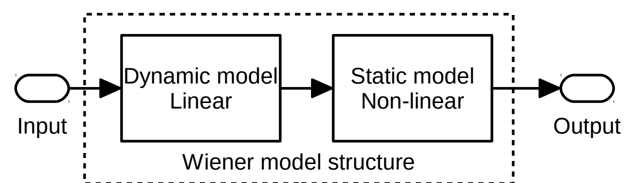

Fig. 3. Wiener model structure

flow variations and sensors readings. The noise is modelled as band-width limited white noise, e.g. characterising variations in material flow or noise in the yield sensor reading.

The relevant actuators, material flows and sensors for the model generation are given in Table 1. By using the modular structure of the presented model additional sensors can be added virtually to facilitate material flow estimation, e.g. of cleaning MOG or HIL simulation of a control system for loss reduction.

Table 1. List of actuators, material flows and sensors relevant for the virtual combine model.

Actuator	Material flow	Sensors
Rotor speed Concave spacing	Total throughput Separation loss Threshing loss Broken grain	Rotor torque Separation loss
Fan speed Upper sieve spacing Lower sieve spacing	Grain throughput Cleaning grain loss Grain tailings MOG throughput MOG tailings MOG in grain tank	Yield Cleaning loss Tailings Grain moisture

3. MODEL GENERATION

The virtual combine is built using data acquired from a large number of data sets obtained from both laboratory and field experiments. The dynamic parameters can be obtained from the standard machine sensors. Steady-state material flows collected in laboratory test stands are more consistent and repeatable than field data and provide more options for designed experiments. However laboratory experiments are more time consuming and requires large amounts of material to be stored.

The steps towards generation of the virtual combine model are as follows

- Data collection
- Obtaining time constants, time delays, steady-state values stochastic variables
- Generating individual trend fits
- Compile models for all sub-modules
- Compile virtual combine from sub-modules

The first step is acquisition of data sets from designed experiments or measurements acquired for other purposes that can be useful for modelling. The material flows to be obtained in order generate a material flow model are given in Table 1 for upper and lower block for threshing/separation and cleaning shoe respectively.

From the acquired data sets dynamic parameters and steady-state values are obtained as will be described in Section 4. From the obtained steady-state values fitted trends representing material flows and sensor readings are generated. This is the most time consuming and challenging part of the modelling process. Initially it requires mapping of the relationships between material flow, actuator excitation and sensor measurements.

Subsequently an evaluation of the interdependencies in order to obtain a mathematically description that provides an adequate representation of the chosen linear or non-linear relationship.

A model for each of the four main components (sub-modules) in the block diagram in Fig. 1 are generated from the obtained dynamic and stochastic parameters, as well as fitted trends obtained from laboratory and field data. The modular structure facilitates the individual system parameters and modelled trends to be utilised for online state estimators, model based control or fault detection.

The last step is compilation of the virtual combine which connects all the materials flows of the sub-modules to one model that describes the material flow throughout the machine.

4. PARAMETER ESTIMATION

The parameter estimation process often requires analysis of several hundred data sets which each contain numerous sensor values. This calls for an automatic or semi-automatic routine for detecting steady-state periods, time constants, time delays and stochastic variables from the available data sets.

Fig. 4 shows collected field data from a Massey Ferguson 9540 driving from headland an into a crop row at constant forward speed. In the top plot the forward speed is shown, the middle plot shows the hydraulic oil pressure from the rotor belt drive variator which is roughly proportional to the rotor torque and the yield sensor in the lower plot. The step response observed for the rotor pressure and yield sensor plot will be modelled using a first order average filter. The time delay between the rotor pressure and yield sensor impact is modelled by a delay chain. Steady-state values are obtained from $15s - 60s$. Finally the stochastic variables will be obtained from the data in the steady-state period.

4.1 Steady-state

All data sets are evaluated using a Steady-State Detection (SSD) algorithm (Kelly and Hedengren, 2013). In order to obtain a steady-state set the relevant actuators and sensors for the relationship are all required to be in steady-state. E.g. for the rotor pressure sensor steady-state would be required for forward speed, rotor speed, concave spacing and rotor pressure sensor. The steady-state set is then obtained from the averages in the joint steady-state period.

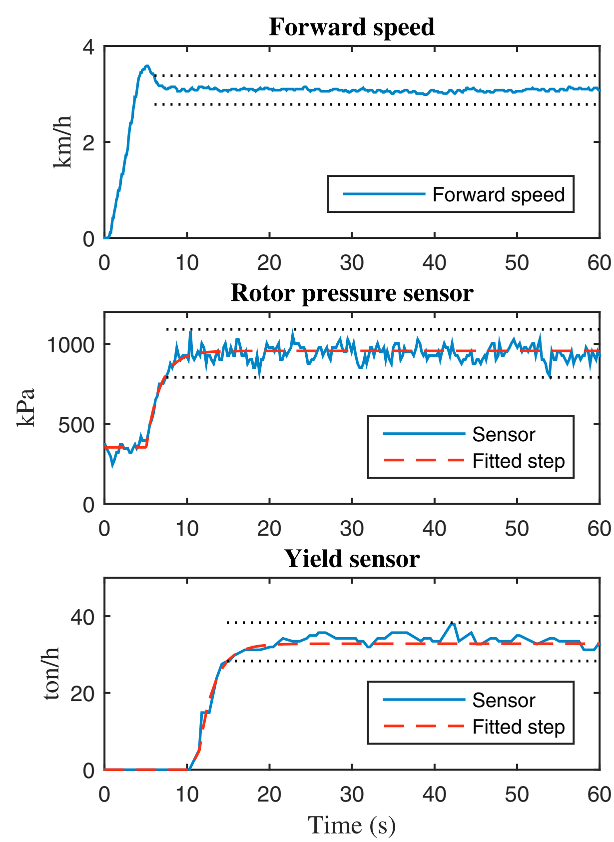

Fig. 4. Automatic steady-state detection. Top plot shows forward speed, middle plot rotor pressure and bottom plot the yield sensor. Steady-state periods are marked with dashed black lines.

4.2 Time constants

The first order time constants τ are obtained using a first order unit step function

$$f(x) = \begin{cases} b + a(1 - e^{-(t-t_s)/\tau}) & \text{if } t \geq t_s \\ b & \text{else} \end{cases}, \quad (1)$$

where the step response starts at t_s for the time t, with b as the steady-state value before the step occurs with step size a. The modelled time constants are obtained as an average of the observed time constants τ from several data sets, see Fig. 5.

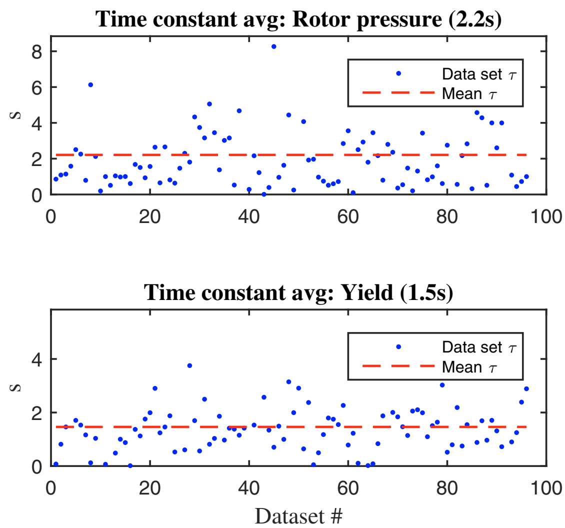

Fig. 5. Combine first order time constant statistic for rotor pressure and yield sensor

4.3 Time delays

Transport time delays are occurring at several locations in the machine. The dominant time constants to be identified are

- Header to threshing and separation unit
- Threshing and separation unit to cleaning shoe (material pan delay)
- Tailings return system
- Elevator for yield sensor reading

In Fig. 4 the delay is evident from the rotor pressure step ($t_{s,r}$) after $5s$ and yield step ($t_{s,y}$) after $11s$. The tailings return delay can be found by opening the upper sieve and closing the lower sieve in order to achieve a high tailings volume that is observable using the yield sensor, see Fig. 6. The figure shows the yield sensor reading where Eq. (1) is fitted to the first step for material impact in the cleaning system (black) and again to the second step caused by the tailings return material (red). The tailings delay is found to be $6s$.

4.4 Stochastic variables

In practical systems various noise sources contribute to the reading at the individual sensors located in the combine. E.g. for the rotor pressure sensor noise are contributed from electrical magnetic noise are picked up in the cable, crop variations in hydraulic oil temperature, noise originating from variations in the field crop density, feeding

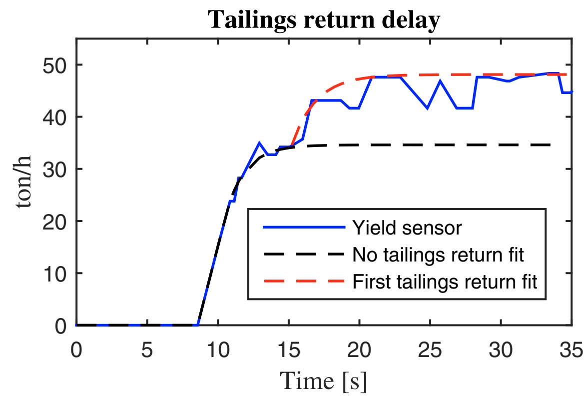

Fig. 6. Combine tailings delay

variations to the rotor etc. Where the dynamic parameters and the steady-state fits represent the general trends in the machine, the stochastic model represents the real variations occurring in the machine in order to increase the realism of the simulated material flows and sensor output. For the simulation model the noise is modelled using data obtained during the steady-state period in Fig. 4. The noise is modelled as bandwidth limited white noise, see noise model in Fig. 7. The model is given by the

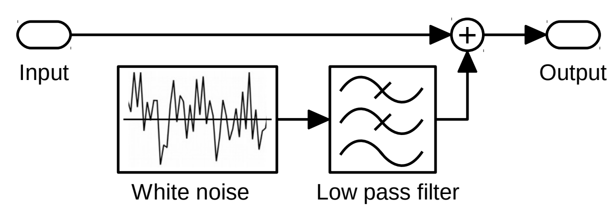

Fig. 7. Stochastic noise model

white noise variance σ_n^2 and bandwidth ω_n of the low-pass filter $H(\omega_n)$. For the rotor pressure sensor σ_n^2 is obtained from the variance of the steady-state period. In order to obtain the noise band-width parameter ω_n the Power Spectral Density function (PSD) S_{yy} is utilised, see Fig. 8. The parameter ω_n is obtained by solving the optimisation problem in Eq. (2) for the data set y obtained from the steady-state period.

$$\arg\min_{\omega_n} = ||S_{yy}(\mathbf{y})/\sigma_n^2 - |H(\omega_n)|^2|| \quad (2)$$

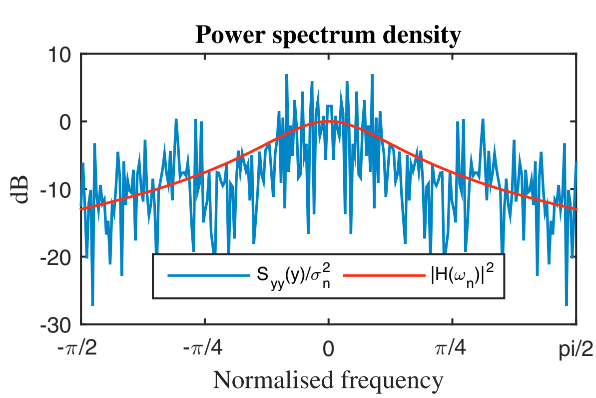

Fig. 8. Rotor pressure power spectrum density

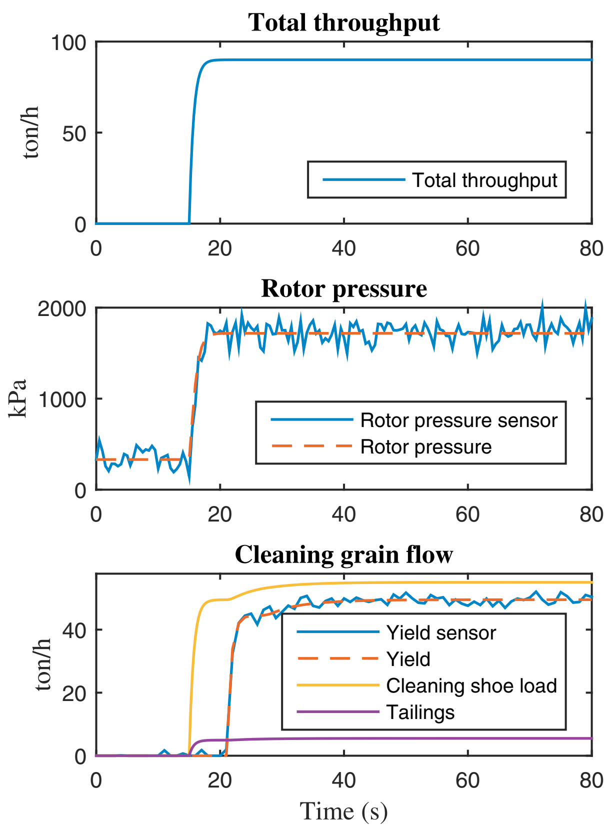

Fig. 9. Simulation of rotor pressure and yield sensor value for step input

5. SIMULATION RESULTS

When all the dynamic, steady-state and stochastic parameters are obtained for the four individual sub-models in Fig. 1, the full model for the virtual combine can be compiled. The interface between the individual sub-models is the material flow of grain and MOG in (ton/h). The simulation will provide the current state (material flow) and the associated sensor readings for the given throughput and actuator settings.

The simulation results are shown in Fig. 9 for a step response occurring after $15s$.

The total throughput from the straw elevator is shown in the top plot. For a practical measurement the total throughput would also have a stochastic component, however it is disabled in the plot in order to clarify the difference between the actual material flows (state).

In the middle plot the rotor pressure is shown as the true value (dashed) and the stochastic component (solid) corresponding to the actual sensor reading from the machine.

As for the rotor pressure sensor the true yield sensor flow is shown with the dashed line and the sensor output with a solid line. For the lower plot the actual shoe load is added to the plot with yield sensor. The delay from the tailings return loop of $6s$ is clearly visible in the extra contribution added to the grain load after $23s$. Compared to the field data in Fig. 4 a similar noise level and time response is observed, hence the model is considered to provide a reasonable good simulation result. However, as seen in Fig. 5 the time constant vary significantly between various runs in the same field.

6. CONCLUSION

A generalised data-driven model structure for at combine harvester is presented, that models the actual material flow using a combination of average filters, time delays, fitted trends, and a bandwidth limited white noise stochastic model.

The model generation procedure is outlined with examples of how to obtain the model parameters from field data. The average filter time constants and time delays where found by fitting a first order step response, detection of steady-state periods using a SSD algorithm and stochastic model parameters using PSD from the steady-state period.

Simulation results were presented for the generated model with parameters obtained field data. Using the modular structure of the presented model additional sensors can be added virtually to facilitate material flow estimation, e.g. of cleaning MOG or HIL simulation of a control system for loss reduction.

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